GMDH Application for autonomous mobile robot's control system construction

A.V. Tyryshkin, A.A. Andrakhanov, A.A. Orlov

Tomsk State University of Control Systems and Radioelectronics, 40 Lenina Prospect, Tomsk 634050, Russian Federation

taw@tcde.ru, rim1282@mail.ru, andrey_a_orlov@mail.ru

Abstract. *Fundamentals of autonomous mobile robot's (AMR) control system construction based on inductive approach of models' self-organization are considered. Close connection of control problem with recognition as well as their connection with objective parameters of AMR are shown. It was demonstrated that it is necessary to perform obstacle recognition allowing for system internal parameters for more effective AMR control (i.e. allowing for conditional obstacles' region). Inductive approach of AMR control system construction on basis of Method of Data Handling (GMDH) is proposed. Inductively found objective functions and function of objects' classification according to obstacle/not obstacle property for autonomous cranberry harvester.*

Keywords

GMDH, autonomous mobile robot, obstacle recognition,
objective function

1 Introduction

Nowadays scientific achievements in pattern recognition and complex technical object control have led humanity to creation of various purpose autonomous mobile robots (AMR) [1]. Currently there are a lot of approaches used for implementation of that systems such as artificial neural network, fuzzy logic, genetic algorithms, autonomous adaptive control etc., or combination of different methods [1]. Another technique based on inductive GMDH and applied efficiently to artificial intelligence interpolation problem solution, nonlinear system identification, pattern recognition, forecasting etc, is known as well [2-4]. In spite of a great variety of successful practical applications of this method, its application to the problem of autonomous robot's control is very uncommon. Particularly, application of polynomial neural network (PNN) to AMR path-planning [5,6] and application of iteration GMDH algorithm to submarine AMR control are known [7]. Authors consider that GMDH can be widely used in implementation of AMR motion control subsystem and other subsystems meant for accompanying problems' solution such as obstacle recognition and robot objective function finding.

2 Inductive approach to construction of AMR control systems

AMR structure [3] shown in fig.1 is proposed according to problems of robot design.

Agreed notations in fig.1: ρ^* – object structure information; L,h,w – object geometrics; t^0 – object temperature information; {P} – set of object parameters; {X} – set of position coordinates; {S} – set of system objective parameters; m – mass of AMR; {T} – set of parameters defining technical state of robot; {U} – set of control actions; {E} – set of autonomous energy storage parameters.

As can be seen from fig.1, decision making is accomplished subject to signals from object recognition system as well as from other subsystems, because the same object can be classified both as obstacle and as non-obstacle depending on internal parameters [8]. Thus, object recognition problem doesn't reduce only to discovery of separating functions in object attribute space. This problem is considered in detail in papers [8,9].

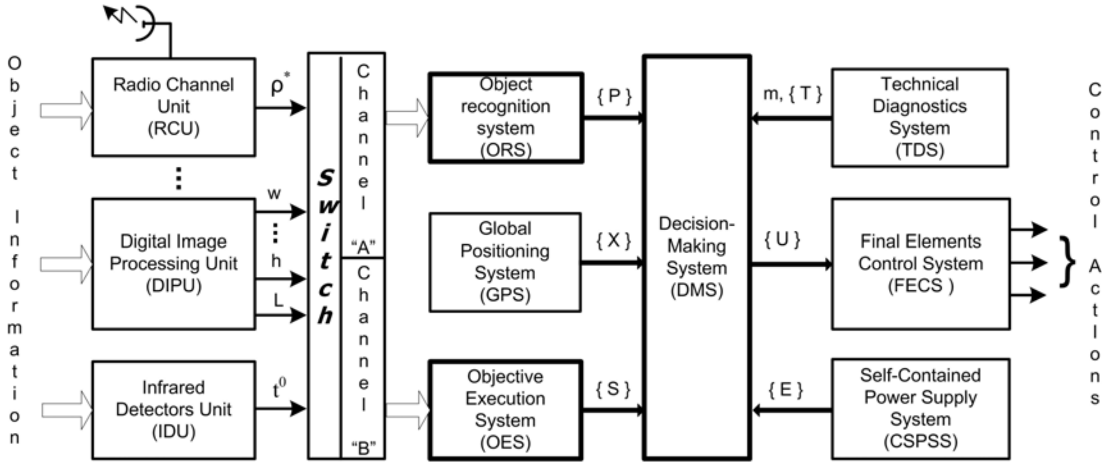

Fig. 1. Generalized structure of AMR

As for OES, usually the objective function is explicitly or implicitly built into AMR control system at the design stage. The problem of objective functions' transformation and artificial neural networks' technology application for its finding is considered in paper [10]. Authors of paper [9] suggested to use GMDH to find objective functions and solve other problems connected with OES.

Questions of obstacle recognition and objective functions finding for autonomous cranberry harvester operational in conditions of floating bog of Tomsk Region designed by authors are considered in detail below.

2.1 Object recognition problem

In papers [5,6] polynomial neural network was used to solve a problem of obstacle avoidance and path-planning. And law was found by defining data sample, which contains information about paths of obstacle rounding. This approach doesn't demand solution of obstacle recognition problem. Besides, it is applicable only in conditions of known static or weakly dynamic environment. It is necessary to determine objects' parameters and to find separating function for operation in conditions of floating bog. Besides, the output variable becomes discrete. Effectiveness of polynomial neural networks application to pattern classification problem was showed in a set of papers [11-13]. Results' comparison of PNN and other neural networks' methods, mentioned in paper [13], indicates that PNN usage provides at least no bigger percentage of errors on training sample. Paper [12] shows that usage of basic PNN model wasn't able to provide required percentage of successful recognition, so approach, based on modified polynomial neural network, was utilized. The main difference of the introduced method consists in feed of input variables not only to the first network layer, but to every following layer while an external criterion error is decreasing. Data sample information and experiments results are provided below.

Data consists of 92 learning samples and 50 training samples. The following variables were chosen as input variables: object length L (m), object width w (m), object height h (m), object temperature t° (°C) and relative dielectric conductivity ε. Geometrics of object (L,w,h) are obtained by image analysis, edge-point linking and feature extraction. Object temperature information is provided by Infrared Detectors Unit (fig.1) after an execution of infrared spectrum image analysis. Taking into account the dielectric conductivity allows to estimate object nature (biological or artificial, metal or dielectric) and, in case of "dielectric", roughly determine object material.

According to features of environment and harvester the following assumptions were made on data sample's design: a set of environment objects is strictly limited; object geometrics are in the range from 0 to 20 m; air temperature changes within the range from -5 to +25 °C; harvester is allowed to overcome non-biological dielectric obstacles with height less than 0.2 m.

Polynomial neural network of obstacles recognition is shown in fig.2. A number on neurons selected on every layer is 4 according to equation provided in paper [11]. Network provides regularity criterion value of 0.055 and percentage of errors on training sample of 12%. Floating bog is an open space with a small amount of obstacles and a relatively small probability to meet biological object, so such percentage of errors is an acceptable result. It should be noted that harvester is provided with front tactile sensor for erroneous recognition disaster protection.

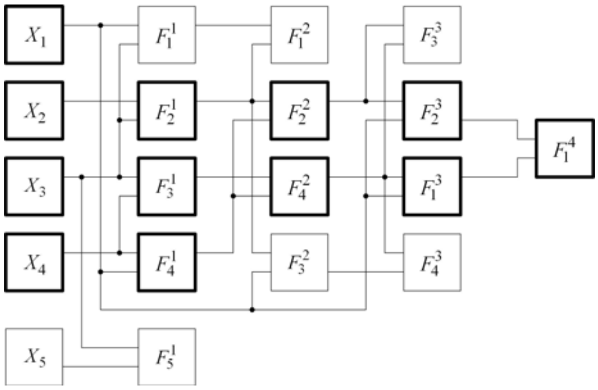

Fig. 2. Modified polynomial neural network structure for obstacle recognition

Neurons' equations have the following forms:

$$F_2^1 = 0.7512 - 0.0071 \cdot w \cdot h - 0.0034 \cdot h^2 - 0.0062 \cdot w^2 + 0.0707 \cdot h + 0.0855 \cdot w$$

$$F_3^1 = 0.7673 - 4.569 \cdot 10^{-5} \cdot h \cdot t - 2.157 \cdot 10^{-7} \cdot t^2 - 0.0033 \cdot h^2 + 0.0004 \cdot t + 0.0700 \cdot h$$

$$F_4^1 = 0.9573 + 9.4863 \cdot 10^{-5} \cdot L \cdot t - 2.500 \cdot 10^{-7} \cdot t^2 + 0.0003 \cdot L^2 + 0.0003 \cdot t - 0.0500 \cdot L$$

$$F_2^2 = -14.805 - 11.213 \cdot F_2^1 \cdot F_4^1 + 1.8830 \cdot \left(F_4^1\right)^2 - 7.9610 \cdot \left(F_2^1\right)^2 + 7.0944 \cdot F_4^1 + 26.054 \cdot F_2^1$$

$$F_4^2 = -11.692 - 7.0954 \cdot F_3^1 \cdot F_4^1 + 0.3786 \cdot \left(F_4^1\right)^2 - 7.0856 \cdot \left(F_3^1\right)^2 + 5.8304 \cdot F_4^1 + 20.631 \cdot F_3^1$$

$$F_2^3 = -2.7575 - 0.2089 \cdot F_2^2 \cdot L - 0.0060 \cdot L^2 - 3.0244 \cdot \left(F_2^2\right)^2 + 0.2438 \cdot L + 6.7788 \cdot F_2^2$$

$$F_1^3 = -6.290 - 0.3085 \cdot F_4^2 \cdot L - 0.0054 \cdot L^2 - 7.296 \cdot \left(F_4^2\right)^2 + 0.3526 \cdot L + 14.5629 \cdot F_4^2$$

$$F_1^4 = -1.3182 - 3.2282 \cdot F_1^3 \cdot F_2^3 + 1.5832 \cdot \left(F_2^3\right)^2 - 0.0329 \cdot \left(F_1^3\right)^2 + 0.6605 \cdot F_2^3 + 3.3386 \cdot F_1^3$$

Output function threshold value was set 0.5 (obstacle if $F_4^1 \geq 0.5$). It should be noted that output function isn't ε parameter-dependent.

2.2 AMR Objective functions' finding

First of all, it should be outlined that all objective functions can be divided into life-support and mission functions. Life-support functions refer to autonomous energy supply supervision, technical state supervision of main AMR units and suitability supervision (if objectives' execution can lead to system breakdown). For simplicity, life-support is meant as autonomous energy supply supervision (fuel margin, energy of accumulator battery). Also, suitability supervision can be reduced to simple rule, that terminates cranberry harvesting till robot's unload if harvest container was overflowed and robot's mass exceeded the limit.

The following mission objective functions of autonomous cranberry harvester can be marked out: $F(m_{cranberry}, \Delta t)$ - maximal cranberry harvest in preset time; $F(m_{cranberry}, t)$ - maximal harvesting speed (maximal cranberry harvest in minimal time); $F(m_{cranberry}, p_{fuel})$ - maximal cranberry harvest with minimal fuel consumption.

Data consists of 280 samples divided into the equal learning and training parts. The following system parameters were chosen as main parameters of current AMR in modeling stage: $\rho_{cranberry}$ (kg/m^2) - surface density of cranberry distribution per 1 m^2; $V_{average}$ (km/h) - average AMR speed per 1 step; Δt (h) – cranberry harvest time interval; P_{fuel} (litres/100km) – AMR engine fuel consumption per 1 step; η (%) – cranberry harvesting efficiency.

One AMR step corresponds to coverage a distance of 1 meter, and because of width of harvesting unit active device is equal to 1.2 meter, AMR is able to harvest 1.2 m^2 of floating bog surface area per 1 step.

According to features of environment and harvester the following assumptions were made on sample design: surface density of cranberry distribution are in the range from 0 to 1 kg/m^2; cranberry harvesting efficiency nonlinearly decreases from 75% to 20% while AMR speed increases from 0 to 7 km/h; AMR engine fuel consumption nonlinearly increases while AMR speed increases from 0 to 7 km/h.

Classical combinatorial GMDH algorithm was used to find objective functions, because a number of input variables is small and output variable is continuous (instead of obstacle recognition, where output variable is discrete).

Modeling results are provided below:

$$F\left(m_{cranberry}, \Delta t\right) = 0.057 \cdot \left(\rho_{cranberry}\right)^2 \cdot V_{average} \cdot \eta + 11.86 \cdot \rho_{cranberry} \cdot V_{average} \cdot \eta \cdot \Delta t + 0.012 \cdot V_{average} \cdot \eta \cdot (\Delta t)^2 \quad (1)$$

$$F\left(m_{cranberry}, t\right) = 6.684 \cdot 10^{-3} \cdot \eta^2 + 11.77 \cdot \rho_{cranberry} \cdot V_{average} \cdot \eta + 0.693 \cdot \rho_{cranberry} \cdot \left(V_{average}\right)^2 \cdot t \quad (2)$$

$$F\left(m_{cranberry}, m_{fuel}\right) = -4.874 \cdot 10^{-3} \cdot \rho_{cranberry} \cdot \eta^2 + 37.4 \cdot \left(V_{average}\right)^2 \cdot \frac{1}{P_{fuel}} + 1257 \cdot \rho_{cranberry} \cdot \eta \cdot \frac{1}{P_{fuel}} \quad (3)$$

Values of regulation criterion are 3.8e-4, 8.6e-3 and 1.8e-3 for equations (1), (2) and (3) respectively. Model's cross criterion of bias was proposed in paper [2]. Values of this criterion are 9.8e-3, 0.9 and 1.6, respectively. It should be noted that both equations comprises terms which correspond physical laws.

3 Conclusion

Acceptable accuracy of modeling results allows to suggest to use GMDH for solution of various problems connected with AMR control. Thus, this leads to program modules' unification that simplifies robot's construction.

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